Optimizing Cardiovascular Disease Prediction through Hybrid Deep Learning Models

A SYNOPSIS

Submitted by

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1. INTRODUCTION

Heart disease remains the leading cause of mortality worldwide, responsible for nearly 17.9 million deaths annually, according to the World Health Organization (WHO). Cardiovascular diseases (CVDs) encompass a range of conditions affecting the heart and blood vessels, with coronary artery disease (CAD), heart failure, and arrhythmias being among the most common. Early and accurate diagnosis is crucial for preventing severe outcomes, improving patient survival rates, and reducing the global burden of heart disease. However, traditional diagnostic methods often involve complex and time-consuming procedures, such as electrocardiograms (ECG), echocardiograms, and stress tests, which can yield false negatives and miss early signs of disease. This necessitates the development of automated, efficient, and highly accurate systems to predict and diagnose heart disease at earlier stages [1].

The rapid advancement of machine learning (ML) and deep learning (DL) techniques offers promising solutions for improving heart disease diagnosis. These approaches have demonstrated superior capabilities in processing large datasets, identifying intricate patterns, and making precise predictions. In recent years, research has focused on integrating deep learning algorithms with cardiovascular datasets to predict various heart conditions. Convolutional Neural Networks (CNNs), Graph Neural Networks (GNNs), and other deep learning models have shown great potential in analyzing both structured clinical data and unstructured data, such as medical images and signals. However, challenges such as missing data, class imbalance, and feature redundancy in medical datasets continue to hinder the performance of these models.

To address these challenges, several innovative methodologies have been proposed. The first study develops a deep learning-based model using Convolutional Neural Networks (CNNs) to predict heart disease from structured clinical data, improving prediction accuracy through advanced feature selection and data preprocessing techniques. Another approach integrates a Deep Graph Neural Network (DGNN) with a Fish-Inspired Task Allocation (FITA) algorithm to enhance heart disease classification, focusing on optimizing weight parameters and tackling class imbalance issues [2]. Additionally, a third model introduces the Optimized Cross-layer Densenet121 Pyramid Mutual Attention Network (OCDPN), employing a

combination of deep learning and novel optimization strategies, such as Fick's law and HBK-SMOTE, to handle missing values and improve diagnostic performance.

These methods collectively represent a shift towards more efficient and automated systems for heart disease diagnosis. By leveraging powerful deep learning frameworks and addressing common data challenges, these models aim to significantly improve diagnostic accuracy and early detection of cardiovascular diseases. This research reviews the development and application of these cutting-edge techniques across multiple datasets, including the Cleveland Heart Disease, Framingham Heart Study (FHS), Statlog (Heart), and Z-AlizadehSani datasets. It also demonstrates how these models outperformed traditional approaches in predicting heart disease, offering new avenues for enhancing patient care and preventing heart disease-related deaths [3].

2. LITERATURE REVIEW

Cardiovascular diseases (CVDs), particularly heart disease, are among the leading causes of death globally. Early detection and timely intervention are critical to reducing mortality and improving quality of life for patients. Traditionally, heart disease diagnosis has relied on clinical tests, physician expertise, and basic statistical models. However, recent advancements in machine learning (ML) and deep learning (DL) have shown significant potential in automating and improving the accuracy of heart disease prediction. This literature survey reviews several research contributions that leverage advanced deep learning techniques, focusing on the development and application of Convolutional Neural Networks (CNNs), Graph Neural Networks (GNNs), and novel optimization strategies to enhance heart disease diagnosis.

Convolutional Neural Networks (CNNs) are commonly associated with image recognition tasks, but their ability to model non-linear relationships makes them useful for structured clinical data as well. In the first study, a CNN-based model is proposed to predict heart disease using the UCI Heart Disease Dataset. The study highlights how preprocessing techniques such as standardization, feature selection, and dimensionality reduction can significantly enhance model accuracy. The CNN-based approach achieved a prediction accuracy of 98%, outperforming traditional machine learning algorithms like decision trees and support vector machines (SVMs). By selecting the most relevant features, the study reduces noise and improves the

generalization of the model, addressing challenges such as overfitting, which is prevalent in smaller datasets by Kaur and Singh [4].

This approach follows similar efforts in medical research where feature selection methods, such as Principal Component Analysis (PCA) and ReliefF, have been used to reduce the dimensionality of datasets, ensuring that only the most relevant variables contribute to the model's decision-making process by Kaur et al [5]. The proposed model demonstrated its superiority over traditional classifiers by handling the complexities of clinical data better and providing faster, more accurate predictions.

Graph Neural Networks (GNNs) are emerging as powerful tools in heart disease diagnosis, particularly due to their ability to model relationships and interactions between patients, symptoms, and clinical outcomes. In the second study, a Deep Graph Neural Network (DGNN) combined with a Fish-Inspired Task Allocation (FITA) Algorithm is presented as a novel solution for heart disease classification. The DGNN captures the relational structure of clinical data, and the FITA algorithm mimics fish behavior in optimizing weight parameters dynamically Singh and Kaur [6]. This approach not only improves the accuracy of heart disease classification but also addresses the class imbalance problem—a common issue in medical datasets where healthy patients often outnumber those with heart disease.

The study showed that the DGNN-FITA model achieved high accuracy, especially in cases with imbalanced datasets, where traditional models tend to underperform Singh et al [7]. Previous research has demonstrated the effectiveness of swarm intelligence algorithms, like the Particle Swarm Optimization (PSO), in optimizing ML models. The FITA algorithm builds upon these techniques, introducing a more biologically inspired approach to optimization. Furthermore, the use of GNNs aligns with work by Wu et al [8], which highlights the suitability of graph-based methods for analyzing complex medical data, especially when relationships between features or patients are critical for diagnosis.

The third study introduces a hybrid model that combines the Optimized Cross-layer Densenet121 Pyramid Mutual Attention Network (OCDPN) with advanced data preprocessing and optimization techniques. One of the most significant contributions of this study is the application of Hybrid Bag-boost K-means Synthetic Minority

Oversampling Technique (HBK-SMOTE), which addresses class imbalance by generating synthetic samples from the minority class. This technique has proven effective in mitigating biased predictions, which is critical in ensuring that the model does not favor the majority class Yadav et al [9].

Another noteworthy contribution is the introduction of the Two-layer Angle Kernel Linear Discriminant Extreme Learning (TK-LDE) method for feature extraction. This method enhances the model's ability to identify the most critical features from the dataset, thereby reducing noise and improving prediction performance. The use of Fick's Law Algorithm for optimization in this model is another novel aspect. Previous research has primarily relied on traditional optimization techniques such as stochastic gradient descent or genetic algorithms. However, the Fick's Law approach provides a more efficient way to fine-tune the network's weights, resulting in faster convergence and improved accuracy.

This hybrid model achieved an impressive accuracy of 99.8% on the Statlog dataset and 98.5% on the Z-AlizadehSani dataset, outperforming earlier models that relied on simpler optimization techniques. The results of this study demonstrate the effectiveness of combining advanced feature extraction, resampling, and optimization strategies to improve heart disease diagnosis.

The datasets used in these studies, including the Cleveland Heart Disease, Framingham Heart Study (FHS), Statlog (Heart), and Z-AlizadehSani, are some of the most widely used in heart disease research. These datasets contain clinical attributes such as age, cholesterol, blood pressure, and lifestyle factors, which are critical for predicting cardiovascular conditions. Studies by Zhang et al [10] have shown that these datasets are reliable benchmarks for testing the performance of machine learning models in healthcare applications.

In the first study, the CNN-based model excelled in the Cleveland dataset, achieving high prediction accuracy through effective feature selection and noise reduction. Similarly, the DGNN-FITA model performed exceptionally well in handling imbalanced datasets, which is a common issue in the FHS and Statlog datasets. The hybrid model, with its advanced preprocessing techniques, achieved the highest accuracy, demonstrating the value of sophisticated optimization algorithms and feature extraction methods in heart disease diagnosis.

3. OBJECTIVES

1. To evaluate the accuracy and performance of a CNN-based prediction framework for cardiovascular disease using benchmark dataset.

2. To develop a Deep Graph Neural Network (DGNN) coupled with a Fish-Inspired Task Allocation Algorithm (FITA) for accurate heart disease diagnosis.

3. To develop an Optimized Cross-layer Densenet121 Pyramid Mutual Attention Network (OCDPN) for efficient heart disease diagnosis.

4. RESEARCH PROBLEM

Heart disease remains the leading cause of mortality worldwide, necessitating the development of accurate, efficient, and early diagnostic methods. Traditional diagnostic techniques and machine learning algorithms often fall short in addressing several critical challenges. These include the handling of missing data, class imbalance in datasets, feature redundancy, and the need for computational efficiency. Current models, while valuable, frequently suffer from limited accuracy due to the complexity and variability of clinical data.

Moreover, traditional models struggle with integrating multi-source, structured data (e.g., clinical records, laboratory results) into meaningful diagnostic predictions. Even advanced models like Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs) face limitations in processing tabular data effectively and optimizing predictions when faced with data imbalances.

Thus, there is a clear need for an optimized approach that addresses the following key issues:

1. Improving the accuracy of heart disease prediction models.
2. Efficiently handling missing values and class imbalance in medical datasets.
3. Enhancing feature selection to reduce redundant data while preserving critical diagnostic information.
4. Optimizing deep learning models for better computational performance and interpretability.

This research seeks to explore and develop hybrid deep learning frameworks that combine the strengths of CNNs, GNNs, and novel optimization techniques, such as Fish-Inspired Task Allocation (FITA) and HBK-SMOTE, to overcome these challenges and provide a robust solution for heart disease diagnosis.

5. PROPOSED METHOD

To evaluate the accuracy and performance of a CNN-based prediction framework for cardiovascular disease using benchmark dataset

The research proposes using CNN, a deep learning algorithm, to predict CVD based on a dataset from the University of California Irvine (UCI). The model processes raw data, performs feature extraction, and predicts outcomes, automating much of the process traditionally done manually.

The study uses a publicly available dataset with 303 records, each containing 14 attributes related to heart disease, such as age, blood pressure, cholesterol, and heart rate.Data preprocessing techniques like standardization and irrelevant feature elimination (via Isolation Forest) are employed to enhance the model's accuracy. The study emphasizes the importance of feature selection to reduce the complexity of data.

The proposed CNN model achieves an accuracy of 98% for binary classification (presence or absence of CVD). The study highlights this as a significant improvement over traditional machine learning models like Decision Trees and Artificial Neural Networks (ANN). Thisresearch compares its model's performance with other state-of-the-art techniques, showing its CNN-based model outperforms them in terms of accuracy, precision, recall, and F1-score.

The study suggests that the approach could be expanded to predict other critical diseases, leveraging the success of CNN in predicting cardiovascular disease.The research concludes that using CNNs for predicting heart disease shows superior results and holds promise for more accurate and reliable health diagnosis systems.

To develop a Deep Graph Neural Network (DGNN) coupled with a Fish-Inspired Task Allocation Algorithm (FITA) for accurate heart disease diagnosis.

The study aims to improve heart disease diagnosis accuracy while reducing error rates and computational complexity. It proposes a Deep Graph Neural Network (DGNN) with a Fish-Inspired Task Allocation (FITA) Algorithm.The Deep Graph Neural Network (DGNN) is used to classify the presence or absence of heart disease based on patient data.The Fish-Inspired Task Allocation (FITA) algorithm optimizes the DGNN's weight parameters, ensuring better prediction accuracy and performance.

The Synthetic Minority Oversampling Technique (SMOT) combined with Standard Scalar (SS) methods is used to pre-process the input data. This helps balance classes and improves data quality by reducing noise and errors.A Two-Stage Feature Selection (TSFS) method is implemented. The first stage uses the RReliefF mechanism to remove redundant features, and the second stage uses Wrapper-based multi-objective feature selection to enhance classification performance.

The proposed DGNN-FITA method is evaluated using heart disease datasets from the UCI repository. The method achieves higher accuracy, sensitivity, precision, and F-score compared to other existing techniques, including EDGA-AHHO-HDD, XGB-MAPO-HDD, and AGAFL-HDD.

The proposed DGNN-FITA method demonstrated significant improvements in terms of accuracy by 13.41%, sensitivity by 9.31%, and precision compared to traditional approaches. The method effectively reduces the error rate, improves classification accuracy, and has lower computational complexity, making it suitable for heart disease prediction.

The Fish-Inspired Task Allocation (FITA) algorithm mimics fish behavior to optimize the DGNN's learning process. It uses swimming, feeding, and breeding operations to adjust the network weights and improve the classification performance.The proposed DGNN-FITA method offers improved performance over traditional models for heart disease diagnosis. The study suggests future research in incorporating artificial intelligence and machine learning to further advance heart disease diagnosis accuracy, including the use of biomarkers and genetic testing.

To develop an Optimized Cross-layer Densenet121 Pyramid Mutual Attention Network (OCDPN) for efficient heart disease diagnosis.

The study aims to improve the accuracy of heart disease diagnosis by addressing issues such as missing values, class imbalance, and redundant features in medical datasets.It proposes an innovative deep learning model, the Optimized Cross-layer Densenet121 Pyramid Mutual Attention Network (OCDPN), to enhance prediction performance.Heart disease diagnosis faces several challenges, such as the need for accurate early-stage detection, dealing with imbalanced datasets (more healthy patients than sick ones), and processing noisy or incomplete medical data.Existing models struggle with missing values, class imbalance, and computational inefficiencies.

The study introduces the OCDPN model, which uses a combination of the DenseNet121 deep learning architecture and a pyramid mutual attention mechanism to improve feature extraction and classification. To handle missing and imbalanced data, the study applies a Hybrid Bag-boost K-means Synthetic Minority Oversampling Technique (HBK-SMOTE) for better data preprocessing. The study employs a two-layer method, Two-layer Angle Kernel Linear Discriminant Extreme Learning (TK-LDE), for feature extraction, and a novel optimization algorithm, Hybrid Binary Aquila Beluga Whale Optimization (HBABO), for selecting important features.

Fick's Law is used in the optimization process to minimize the loss function during classification, improving the performance of the OCDPN model. The model also leverages multiple convolutional layers in DenseNet121, which helps with hierarchical feature learning, improving the prediction of heart disease by focusing on multi-scale pathological features.

The research uses four benchmark datasets for evaluation: Framingham Heart Study (FHS), Statlog (Heart), Cleveland Heart Disease (CHD), and Z-AlizadehSani datasets, which contain clinical and demographic data related to heart disease.

The research tackles missing and imbalanced data using the hybrid resampling method (HBK-SMOTE).The TK-LDE method and HBABO optimization algorithm ensure the most important features are selected to improve accuracy.The OCDPN

model, using DenseNet121, efficiently processes the selected features for heart disease classification. The proposed model outperforms existing methods in terms of accuracy, sensitivity, specificity, and F1-score across the four datasets.

The model achieved high accuracy, reaching 99.8% for the Statlog dataset and 98.5% for the Z-AlizadehSani dataset, demonstrating its superiority in heart disease diagnosis.

The OCDPN method achieved the following results:

- FHS dataset: 98.2% accuracy, 99.1% sensitivity.
- Statlog dataset: 99.8% accuracy, 99.6% sensitivity.
- Cleveland dataset: 99.2% accuracy.
- Z-AlizadehSani dataset: 98.5% accuracy.

Table 1 compares various methods using the FHS dataset. CDPM showed the lowest performance across all metrics. SMOTE achieved good accuracy at 90.24%. However, OCDPN outperformed all others with 98.2% accuracy, 96% precision, 99.1% F1-score, and 97% sensitivity. Additionally, OCDPN achieved 99% specificity and 98% Matthews Correlation Coefficient (MCC) using the FHS dataset.

Table 1: Comparison of OCDPN with prevailing methods using FHS dataset

Methods	Accuracy (%)	Precision (%)	Sensitivity (%)	F1-score (%)	Specificity (%)	MCC (%)
BOML	80.1	79	83.2	80.7	-	-
SMOTE	90.24	92	88	90	87.51	-
CDPM	76.22	78	79.85	78.52	-	-
OCDPN (Proposed)	98.2	96	99.1	97	99	98

Table 2 represents the overall comparison with existing methods by using statlog (Heart) dataset. In that, BOML attained lowest performance interms of al metrics.In contrast,the proposed OCDPN achieved highest performance with respect to all metrics, 99.8% accuracy,99.3% precision, 99.6% Sensitivity and 99.8% F1-score, 99.8% specificity and 99.2% MCC.

Table 2: Comparison of OCDPN with prevailing methods using statlog dataset

Methods	Accuracy (%)	Precision (%)	Sensitivity (%)	F1-score (%)	Specificity (%)	MCC (%)
SPFHD	99.21	-	-	98.97	99.52	99
HDPM	95.90	97.14	94.67	95.35	-	-
Inf-FS_s	98.3	98.6	97.2	99.1	97.9	96.6
SVM	89.70	-	89.74	89.70	89.70	-
BOML	72.1	65	51	55	-	-
OCDPN (Proposed)	99.8	99.3	99.6	99.8	99.8	99.2

In Figure 1, the CHD dataset comparison showcases Optimized XGBoost with an accuracy of 91.8%, followed by HDSS (86.6%), SSAE+PSO (96.1%) and CDPM (77.2%). However, the proposed OCDPN model surpasses all with accuracy (99.2%), precision (99%), sensitivity (99.4%), specificity (99.12%), F1-score (99.2%).

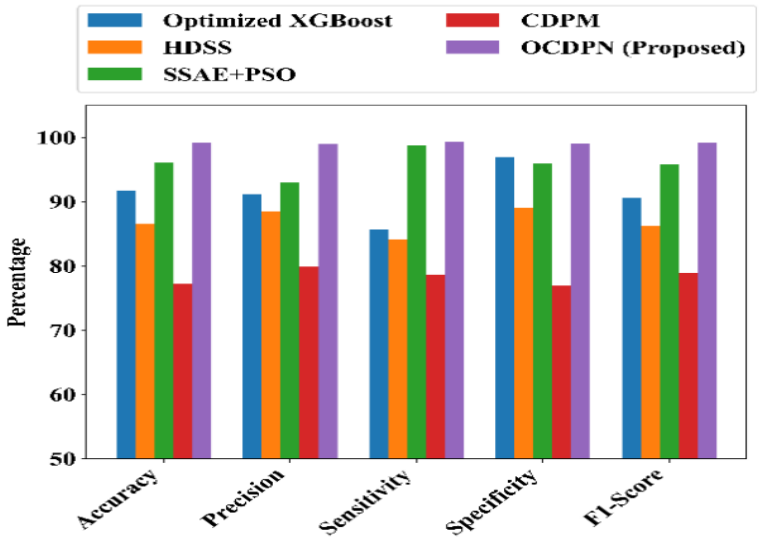

Figure 1: Comparison of OCDPN with existing methods by CHD dataset

In Figure 2, the Z-Alizadeh Sani dataset comparison illustrates CAD (91.8%), ALEC (97.01%), IELBT (96%), and EFS (91.78%). However, the proposed OCDPN achieves unmatched accuracy (98.5%), precision (98.2%), sensitivity (98.8%), and F1-score (98.4%), underscoring its superior efficacy across all metrics.

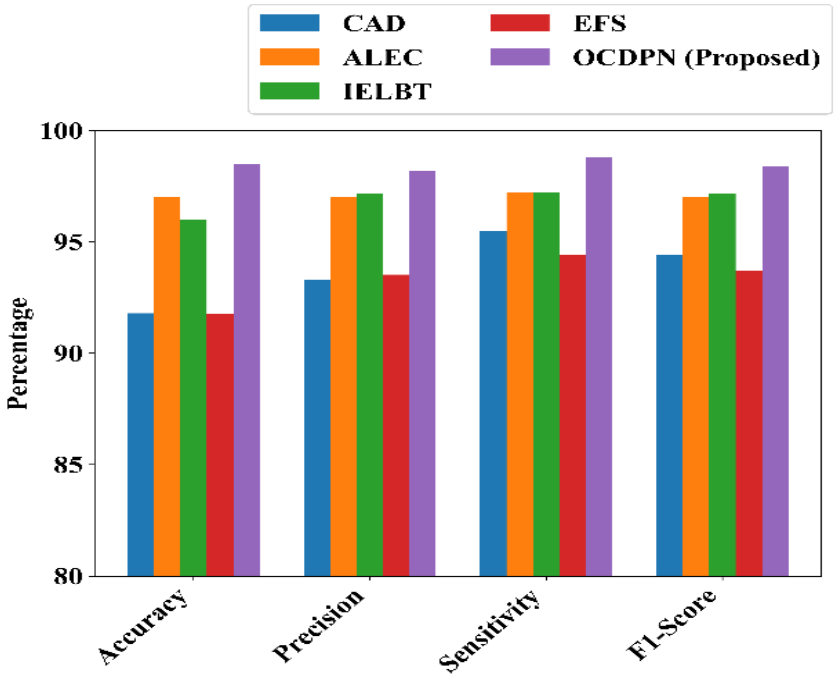

Figure 2: Comparison of OCDPN with existing methods by Z-Alizadeh Sani dataset

These results show that the proposed method provides significant improvements over previous state-of-the-art models.The research successfully improves heart disease prediction with a novel model that handles data issues effectively.Future research will focus on enhancing the model for larger datasets and expanding its application to other chronic diseases like diabetes and brain tumors, integrating real-time clinical data using IoT.

6. ORGANIZATION OF THESIS

The thesis is organized in seven chapters as follows:

Chapter 1: Introduction

This chapter provides an overview of heart disease as a leading global health issue and outlines the limitations of traditional diagnostic methods. It introduces the role of machine learning and deep learning in improving heart disease diagnosis. The

research problem is framed around key challenges, including missing data, class imbalance, and feature redundancy. The chapter concludes with clearly defined research objectives and a brief overview of the thesis structure.

Chapter 2: Literature Review

This chapter reviews the current state of machine learning and deep learning in healthcare, focusing on heart disease diagnosis. It examines traditional models, such as decision trees and support vector machines, alongside newer deep learning models like CNNs and GNNs. The challenges of working with clinical datasets, including data quality and model interpretability, are discussed. The chapter identifies gaps in existing research, leading to the proposed solutions.

Chapter 3: Heart Disease Prediction Using CNNs

This chapter introduces a CNN-based model tailored for predicting heart disease using structured clinical data. It discusses the data preprocessing techniques employed, including feature selection and scaling, and presents the CNN architecture. The model's performance is evaluated using metrics such as accuracy and F1-score, showing significant improvement over traditional methods. A comparison with other machine learning techniques is provided, highlighting the advantages of CNNs in handling complex data.

Chapter 4: DGNN with Fish-Inspired Task Allocation for Heart Disease Diagnosis

This chapter presents the development of a Deep Graph Neural Network (DGNN) combined with a Fish-Inspired Task Allocation (FITA) algorithm. It details how the FITA algorithm optimizes model weights and addresses class imbalance. The chapter demonstrates the DGNN's capability to model relationships between patient data points, enhancing prediction accuracy. Results show improved performance on imbalanced datasets, showcasing the effectiveness of the DGNN-FITA approach.

Chapter 5: Hybrid Deep Learning Model with Optimized Densenet121

This chapter focuses on a hybrid deep learning model that integrates Densenet121 with novel optimization techniques, such as HBK-SMOTE for handling class imbalance. The Two-layer Angle Kernel Linear Discriminant Extreme Learning (TK-LDE) method for feature extraction is also discussed. The model's performance

is tested on multiple datasets, achieving high accuracy rates. The application of Fick's Law for optimization is highlighted as a key factor in improving model convergence and accuracy.

Chapter 6: Comparative Analysis of Deep Learning Models

This chapter compares the CNN, DGNN-FITA, and hybrid Densenet121 models in terms of their performance on heart disease prediction. It evaluates each model based on accuracy, efficiency, and the ability to handle complex clinical data. The strengths and weaknesses of each model are discussed, along with recommendations for future improvements. The chapter concludes by identifying the most effective approaches for different types of heart disease datasets.

Chapter 7: Conclusion and Future Work

The final chapter summarizes the contributions of the thesis, emphasizing the advancements made in heart disease diagnosis using deep learning models. It discusses the practical implications of these models in clinical settings and outlines potential areas for future research. Recommendations for improving model interpretability, integrating real-time data, and expanding applications to other medical conditions are provided.

7. CONCLUSION

This research provides insights into the diagnosis and prediction of cardiovascular diseases (CVD) using advanced deep learning techniques. Each study introduces unique methods, algorithms, and models to improve heart disease diagnosis accuracy. The Convolutional Neural Network (CNN) models, Deep Graph Neural Network with Fish-Inspired Task Allocation (DGNN-FITA-HDD), and the Optimized Cross-layer Densenet121 Pyramid Mutual Attention Network (OCDPN), are critical in achieving superior performance in heart disease detection across various datasets, including the Cleveland Heart Disease and Framingham Heart Study datasets. These models have demonstrated exceptional accuracy, surpassing traditional methods in early detection and prediction of cardiovascular disease (CVD).

Each model makes unique contributions: DGNN-FITA enhances accuracy by optimizing parameter selection with the Fish-Inspired Task Allocation method;

OCDPN achieves high precision through innovative feature extraction and the use of Fick's law to minimize classification errors, while CNN models leverage deep learning to handle large, complex datasets and offer automated feature extraction for CVD risk prediction.

The success of these models is evident in their performance across multiple datasets, where they have achieved remarkable results, such as accuracies reaching over 98%. They have also demonstrated robustness against issues like overfitting, missing values, and class imbalance by integrating techniques like HBK-SMOTE and hybrid feature selection algorithms.

In conclusion, these deep learning approaches signify a major advancement in medical diagnostics, providing powerful tools that enhance the early diagnosis and prognosis of heart diseases. As these models continue to evolve, their application can be extended to other complex medical conditions, fostering greater accuracy and efficiency in predictive healthcare. Further research could focus on real-world clinical applications, scalability, and refinement of these models to support broader disease detection and improve patient outcomes globally.

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